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Abstract: We show that individual investors over-extrapolate from their personal experience when making savings decisions. Investors who experience particularly rewarding outcomes from saving in their 401(k)—a high average and/or low variance return—increase their 401(k) savings rate more than investors who have less rewarding experiences with saving. This finding is not driven by aggregate time-series shocks, income effects, rational learning about investing skill, investor fixed effects, or time-varying investor-level heterogeneity that is correlated with portfolio allocations to stock, bond, and cash asset classes. We discuss implications for the equity premium puzzle and interventions aimed at improving household financial outcomes.

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In this paper, we show that individual investors over-extrapolate from their personal return experience when making savings decisions. *Within a given time period*, investors who experience particularly rewarding outcomes from saving in their 401(k)—a high average and/or a low variance rate of return—increase their 401(k) savings rate more than investors who have less rewarding experiences with saving.

These effects are economically and statistically significant. All else equal, a one standard deviation increase in an investor's 401(k) rate of return during year t increases her 401(k) savings rate at year-end t by 0.13 percentage points of income. A one standard deviation increase in the variance of an investor's 401(k) return during year t lowers her savings rate by 0.16 percentage points at year-end t and 0.34 percentage points at year-end $t + 1$. By comparison, the average annual savings rate change in our sample is 0.30 percentage points.

This behavior is not explained by factors that *should* affect savings rates. We include controls in our regressions to capture aggregate time fixed effects (such as news about the macroeconomy or expected asset returns), employer-specific time fixed effects, investor fixed effects, investor-level income effects, and time-varying investor-level heterogeneity that is correlated with portfolio allocations to stock, bond, and cash asset classes. Thus, our results indicate that savings decisions are affected by random accidents of personal financial history that should not matter to a rational agent.

Our findings are explained by a model in which investors follow a naïve reinforcement-learning heuristic: increase weights on strategies in which you have personally experienced success, even if this past success logically does not predict future success. Erev and Roth (1998) find that a reinforcement-learning model outperforms forward-looking models in predicting how play evolves in a broad range of economics experiments. Charness and Levin (2003) show that when an (optimal) Bayesian updating rule conflicts with a reinforcement-learning rule, experimental subjects' choices shift towards the erroneous option that reinforcement learning recommends. Our analysis demonstrates that these laboratory learning dynamics also apply to real-world financial decisions.

The behavior we document also has implications for the equity premium puzzle. If reinforcement learning exerts an upward force on aggregate savings rates following a positive equity market return (and the reverse for a negative equity market return), then the time-series covariance of aggregate consumption growth with equity market returns will be depressed. Choi (2006) presents a general equilibrium model where investors behave in such a manner. The model generates volatile equity returns, a high equity Sharpe ratio, and low, stable risk-free rates that match the historical U.S. data while maintaining smooth aggregate consumption growth and low investor risk aversion.

Although we do not directly observe the entire savings flow of our 401(k) investors, most households have few financial assets outside of their 401(k). It is therefore likely that the changes in the 401(k) savings rate we observe reflect changes in the total savings rate for most of our sample. When we examine a subset of our sample that has especially strong incentives to adjust their total savings rate via the 401(k) contribution margin—households whose marginal 401(k) contribution garners a matching contribution from their employer—we continue to find evidence of return chasing and variance avoidance in the contribution rate.

Our results complement Barber, Odean, and Strahilevetz (2004), who document brokerage investors' propensity to repurchase individual stocks they previously sold for a gain while shunning individual stocks they previously sold for a loss. Barber, Odean and Strahilevetz find that purchased stocks previously sold for a gain do not subsequently underperform relative to benchmarks based on size and book-to-market. Therefore, conditional on making a purchase, the propensity to buy previously profitable stocks appears to be welfare-neutral. In our setting, however, welfare will generally be affected by changes in an employee's 401(k) contributions, which are tax-advantaged and often garner a matching employer contribution.

Our results are also related to Kaustia and Knüpfer (2008) and Malmendier and Nagel (2007). Kaustia and Knüpfer (2008) show that Finnish investors are more likely to subscribe to future IPOs if they experienced high returns in their prior IPO subscriptions, and posit that this effect is due to reinforcement learning. Malmendier and Nagel (2007) focus on low-frequency responses to variation in return experiences across birth cohorts. They show that cohorts that have experienced high stock market returns throughout their lives hold more stocks, and cohorts that have experienced high inflation throughout their lives hold fewer bonds. We focus on higher-frequency responses, and the disaggregated structure of our data allows us to show that variation in returns *within* a cohort matters as well.

The rest of the paper proceeds as follows. Section I describes our 401(k) data. Section II explains the framework within which we conduct our empirical estimation. Section III presents our results, and Section IV considers alternative interpretations of the results. We conclude in Section V by reconciling our results with the disposition effect and discussing how our findings might inform policy interventions intended to improve household financial outcomes.

I. Data description

Our data come from a large benefits record-keeping firm. We have panel data for five companies that start when our data provider became the plan administrator at each company and end at year-end 2000. These data contain the date, amount, and type of every transaction made in these firms' 401(k) plans by every participant. In addition, we have year-end cross-sectional snapshots from 1998, 1999, and 2000 for all active employees that include demographic information such as their birth date, hire date, gender, compensation, marital status, and state of residence. The year-end cross-sections also contain point-in-time 401(k) information, including the contribution rate in effect during the final pay period of the year, total balances, and asset allocations.

Table I gives summary statistics as of year-end 2000 for our companies, which we code-name Company A through E. Our sample consists of large firms that span a wide range of industries. Equally weighting each company, the employees are on average 42.9 years old and earn $55,292 a year. By comparison, the March 2001 Current Population Survey reports an average age of 40.8 years and average salary of $45,656 among full-time workers in companies employing over 1,000 workers and offering some kind of retirement plan. The average 401(k) participation rate across the firms is 79%, which is close to the 2000 national participation rate of 80% found by the Profit Sharing/401(k) Council of America (2001), and the average balance of participants is $65,964, which is similar to Holden and VanDerhei's (2001) reported average year-end 2000 balance of $61,207 among plans with more than 10,000 participants.

At each of these firms, employees can choose a contribution rate that is an integer percentage of their salary. The contribution rate determines how much of each paycheck is deducted and contributed to the plan, and it remains in effect until the employee actively changes it. All of our companies offer matching contributions proportional to employee contributions up to a threshold, although Company C did not introduce its match until 2000. For example, employees who contributed at least 3% of their pay at Company B received an additional contribution from the company equal to 0.75% their pay.

The large majority of the plans' investment options are mutual funds. Every plan offers at least eight mutual funds, including at least one fixed-income fund. The most important investment option that is not a mutual fund is employer stock, which is offered by four of our five plans. In addition, Companies A and D added a self-directed window to their plans in 2000 and 1999, respectively. Self-directed windows allow participants to buy and sell individual stocks using their 401(k) balances. We do not observe transactions within the self-directed windows, although we do know the total balances held in the windows at each year-end. Among plan participants in Companies A and D, 1.1% and 8.0%, respectively, had any balances in the self-directed window at year-end 2000. Conditional upon having any money in the window, participants in Companies A and D held on average 34.1% and 28.1% of their 401(k) balances in the window, respectively.

All of the plans allow changes to the elected contribution rate and asset allocation on a daily basis. There is no charge for these changes, which can be made by talking to a benefits center representative on the phone during business hours, or by using a touch-tone phone system or the Internet 24 hours a day. With these relatively straightforward methods to make free changes, the transaction costs seem minimal.

II. Empirical methodology

Our empirical objective is to estimate the relationship between an individual's 401(k) contribution rate and the first two moments of 401(k) returns. We compute investor *i*'s monthly 401(k) returns by weighting each fund's arithmetic return by the proportion of the portfolio held in the fund at the prior month-end. We then define $R_{i,t}$ as the arithmetic average of the monthly 401(k) returns in the one-year period *t*. $R_{i,t}$ is meant to capture how lucrative an additional investment in the 401(k) is expected to be if one used only year t's monthly 401(k) returns to infer the future 401(k) return-generating process. It does not necessarily reflect the total percent change in the investor's wealth during t, which also depends upon the pre-existing 401(k) balances and the amount and timing of additional contributions to the 401(k). We will control for total dollar wealth changes later. We define $\sigma^2(R_{i,t})$ as the variance of the twelve monthly returns that comprise $R_{i,t}$.

We adopt a flexible functional form for the determinants of an individual's 401(k) contribution rate. Let $C_{i,t}$ be the 401(k) contribution rate, measured as a percent of salary, in effect for individual i at year-end t. Then

$$C_{i,t} = g_i(age_{i,t}) + \beta_1 R_{i,t} + \beta_2 R_{i,t-1} + \beta_3 \sigma^2(R_{i,t}) + \beta_4 \sigma^2(R_{i,t-1}) + \mathbf{X}_{i,t}\boldsymbol{\gamma} + \varepsilon_{i,t}, \tag{1}$$

where $g_i(\cdot)$ is a function specific to investor i, $age_{i,t}$ is the investor's age, $\mathbf{X}_{i,t}$ is a vector of other control variables defined as of year-end t, and $\varepsilon_{i,t}$ is the residual term. By using the contribution rate in effect at year-end rather than the total contributions during the year, we can be sure that all the information in the explanatory variables was potentially available to the investor before she made her choice of the dependent variable. The function g_i could vary across investors due to unobserved differences (e.g. discount rates, risk aversion, expected income growth, background risk) that alter the optimal solution to the lifecycle consumption-investment problem. By controlling for g, we control for year-over-year contribution changes that would have occurred regardless of 401(k) returns. We include contemporaneous returns $R_{i,t}$ and their variance $\sigma^2(R_{i,t})$ as explanatory variables. We also include lagged returns and the variance of lagged returns, $R_{i,t-1}$ and $\sigma^2(R_{i,t-1})$, to allow for the possibility of a sluggish response to 401(k) performance. At the end of this section, we discuss and motivate the specific control variables contained in $\mathbf{X}_{i,t}$ for each of our specifications.

We assume that the function $g_i(age_{i,t})$ is locally well-approximated by a first-order Taylor expansion around the investor's age at year-end 1999 (the middle year in our sample of contribution rates):

$$g_i(age_{i,t}) \approx g_i(age_{i,1999}) + \frac{\alpha_i}{2}(age_{i,t} - age_{i,1999}) . \tag{2}$$

Substituting (2) into (1) and first-differencing yields an equation with an individual fixed effect in contribution rate changes:

$$\Delta C_{i,t} = \alpha_i + \beta_1 \Delta R_{i,t} + \beta_2 \Delta R_{i,t-1} + \beta_3 \Delta \sigma^2(R_{i,t}) + \beta_4 \Delta \sigma^2(R_{i,t-1}) + \Delta \mathbf{X}_{i,t} \boldsymbol{\gamma} + \Delta \varepsilon_{i,t} . \tag{3}$$

We estimate (3) using least-squares regression. We cluster our standard errors at the company × state × year level in case peer effects or information spillovers cause dependence in contribution rate changes between coworkers in the same office (Duflo and Saez (2003), Hong, Kubik, and Stein (2004), Ivkovich and Weisbenner (2007)).[1]

Contributions to 401(k) plans are usually made with before-tax money. However, some of our sample plans allow contributions using after-tax money as well. We add the before-tax and (if the plan offers the option) after-tax 401(k) contribution rates in effect for the last pay period of 1998, 1999, or 2000 to calculate $C_{i,t}$ in each of these years. We include employees whose contribution rate is zero, provided that they have a positive 401(k) balance.[2] We also require that individuals have salaries greater than $20,000 in 1998 because a large fraction of those with salaries under $20,000 are part-time employees who are likely to direct less attention

[1] Consistent with there being only weak geographic effects in contribution rates, our standard errors are barely affected by clustering relative to assuming that all observations are independent. In contrast, the standard errors in our portfolio return persistence analysis, presented in Section IV.A, are greatly increased by clustering.
[2] Employees with no balances in the plan are excluded from our analysis because our key explanatory variables, which depend on the individual's rate of return on plan assets, are only defined for those with assets in the plan.

to the 401(k) than full-time employees.[3] In addition, we trim workers who have a one-year income growth observation greater than 30% or less than –20%, which roughly corresponds to removing the top 2% and bottom 2% of the income growth distribution. These deleted outliers are likely caused by transitions between part-time and full-time work status.

The presence of the individual fixed effect imposes the requirement that all employees in our regressions have two contribution rate change observations. We also need four full years of capital gains data in order to estimate the coefficients on both contemporaneous and lagged ΔR *and* $\Delta\sigma^2(R)$. Thus, our sample is limited to workers who have been actively employed at a sample firm and continuously enrolled in the 401(k) plan from January 1, 1997 to December 31, 2000. Company E's data start on March 31, 1997, when our data provider assumed administrative services for its plan, so we instead require its workers to be actively employed and continuously enrolled in the plan from March 31, 1997 to December 31, 2000.[4]

Finally, we drop individuals if their 1998 salary is high enough that, by contributing at the plan's maximum before-tax contribution rate, they could exceed the $10,000 statutory limit on 1998 before-tax 401(k) contributions. The reason we impose this selection rule is that a highly paid employee could contribute enough that he hits the before-tax dollar limit midway through the year. For the rest of the year, his before-tax contribution rate is frozen at 0 and does not reflect his desired contribution rate.[5]

All of our specifications include the log of the employee's tenure at the company and company dummies interacted with year dummies in the $\mathbf{X}_{i,t}$ vector. The company × year

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[3] In the March 2001 Current Population Survey, 29.9% of workers who earned less than $20,000 a year worked less than 35 hours a week or fewer than 40 weeks per year. Only 5.6% of workers earning between $20,000 and $30,000 a year satisfied this definition of part-time work.

[4] We assign a zero 401(k) return to Company E employees for the first three months of 1997. Our results are qualitatively similar if we drop Company E from the sample.

dummies control for public news that affects optimal contribution rates in aggregate, as well as news that is specifically relevant to employees of each company.[6]

Even after controlling for time shocks common to each company, one might worry that there is cross-sectional heterogeneity in the time shock that is correlated with 401(k) portfolio returns. One candidate for such a correlated shock is the wealth effect from the 401(k) portfolio capital gain itself. Thus, in many specifications, we also control for individual wealth effects by adding contemporaneous and lagged 401(k) capital gains normalized by current income, $CapitalGain_{i,t}/Y_{i,t}$ and $CapitalGain_{i,t-1}/Y_{i,t}$, where $CapitalGain_{i,t}$ is investor i's 401(k) dollar capital gain during year t and $Y_{i,t}$ is the investor's annual salary. We calculate $CapitalGain_{i,t}$ by taking the difference in balances between year-end t and $t - 1$ and then subtracting contributions, rollovers into the plan, and loan repayments during year t and adding back withdrawals and new loans during year t. We normalize *CapitalGain* (a variable whose unit is dollars) by income because the dependent variable in our regressions (contribution rate) is also expressed as a percent of income.

Another potential concern is that a series of economic news arrived during our sample period that differentially affected the type of people who tend to hold, say, relatively more equities (e.g. news about the return to high-skill human capital). Because asset class allocations are in turn correlated with portfolio returns, this could confound our identification. To account for this possibility, we will control for interactions between year dummies and three variables: the dollar amount of the individual's portfolio held in equities, bonds, and cash at the prior year-end, all as a *fraction of current-year income*. In our most comprehensive specification, we also

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[5] We also drop a small number of Company A employees who are eligible to contribute to the company's deferred compensation plan.

add interactions between year dummies and two variables: the *fraction of one's 401(k)* allocated to equities and to bonds (also at the prior year-end).

Unfortunately, we cannot calculate R and $\sigma^2(R)$—the portfolio percentage return and variance—including returns in the self-directed windows at Companies A and D, since we do not observe monthly window balances. The two capital gains variables, however, do include dollar gains realized in the window. Our contribution rate results are robust to excluding Companies A and D from the sample.

III. Results

A. Summary statistics

The selection criteria described in Section II leave us with 49,248 contribution rate change observations on 24,624 employees.[7] Table II reports summary statistics for contribution rate changes and our portfolio return variables. From 1998 to 2000, the median annual contribution rate change is zero, and the mean change is 0.30 percentage points of income. Between 1998 and 1999, 20.6% of our sample investors changed their contribution rate, and 22.4% changed their contribution rate between 1999 and 2000 (these specific numbers are not reported in the table). Over the two years, 35.1% of investors made at least one contribution rate change.

Pooled across 1997 to 2000, the average monthly 401(k) rate of return, R, has a median of 0.83% and a mean of 0.99%. Reflecting the dramatic late-1990s bull market and subsequent

[6] Because of the presence of individual fixed effects, we will ultimately be able to identify only one fixed effect per company: the difference between the company's fixed effect in 2000 and 1999 minus the difference between the company's fixed effect in 1999 and 1998.
[7] At year-end 2000, there were 134,589 active employees at our companies, of whom 100,527 had enrolled in the 401(k), and 69,286 had been enrolled in the 401(k) since at least January 1, 1997 (or March 31, 1997 in the case of Company E). Most of the observations cut from these 69,286 are due to the income cutoff; no employee remaining in our final sample could exceed the $10,000 statutory limit on 1998 before-tax contributions by contributing at the plan's maximum contribution rate.

crash, R has a wide distribution; its pooled cross-sectional standard deviation is 1.41%. The volatility of monthly portfolio returns, $\sigma^2(R)$, also exhibits wide variation across individuals due to differing portfolio shares allocated to equities and particularly to employer stock. The typical volatility is quite high, since many plan participants held significant amounts of their employer's stock. Our companies' monthly stock returns generally experienced annualized standard deviations well over 100% during the sample period. The dollar capital gain normalized by income, *CapitalGain*/*Y*, has an economically narrower range because most investors' 401(k) balances are modest compared to their income. The mean and median of *CapitalGain*/*Y* are 0.09 and 0.04, respectively, and its standard deviation is 0.30.

B. Main contribution rate regressions

Table III, Panel A presents the coefficients from estimating equation (3) on the full sample. The first column shows estimates from the baseline specification, which includes first-differenced contemporaneous and lagged 401(k) return and volatility, log tenure, and company × year dummies as explanatory variables. We find that a one standard deviation increase in year t's average monthly return causes the 401(k) contribution rate at year-end t to rise by 1.41 × 0.0933 = 0.13 percentage points of income, an effect that is significant at the 1% level. There is no further increase in year $t + 1$.

In contrast, a one standard deviation increase in year t volatility causes the contribution rate at year-end t to fall by 43.80 × 0.0042 = 0.18 percentage points. The contribution rate falls an additional 0.17 percentage points by year-end $t + 1$. Both the contemporaneous and lagged variance-avoidance effects are significant at the 1% level.

To assess the economic significance of these effects, recall that the average annual contribution rate increase is 0.30 percentage points of income. Thus, the 0.13 percentage point effect of 401(k) returns and the 0.35 percentage point two-year effect of volatility are substantial relative to the mean.

Because we are including company × year dummies in our regression, we are controlling for public news about expected asset returns and news specifically relevant to employees of each company. Holding fixed news, an investor should not update his beliefs about the future returns of his 401(k)'s investment options differently based upon how well his own portfolio did. Yet we find that employees do invest more in their 401(k) when their own portfolio performance was relatively good. Because we are including individual fixed effects in our regression, we are also controlling for time-invariant investor heterogeneity—such as risk aversion, time preference, human capital, etc.—that may affect contribution rates.

Our results are robust to controls for cross-sectional heterogeneity in the time shocks. The second column of Table III shows that controlling for wealth effects via the contemporaneous and lagged normalized dollar capital gains in the 401(k) barely affects the coefficients on return and volatility. The third column of Table III adds controls for the dollar amount held in equities, bonds, and cash at the prior year-end, and the fourth column adds controls for the fraction of the 401(k) held in equities or bonds at the prior year-end. Even with these additional controls, we continue to estimate large and statistically significant return chasing and variance avoidance, and the point estimates remain similar to those in the baseline specification of column 1. In the most comprehensive specification, we find that a one standard deviation increase in portfolio returns in year *t* increases the 401(k) contribution rate in year *t* by 0.12 percentage points, and a one standard deviation increase in the volatility of returns in year *t* decreases the 401(k) contribution rate by 0.16 percentage points at year-end t and by another 0.18 percentage points at year-end $t+1$.

We perform several additional robustness checks for our specification. First, we test whether our results are symmetric. In untabulated regressions, we use splines to allow the return and variance effects to vary depending on whether the return or variance in a given year is greater than or less than the prior year's realization. In every case, we find that the asymmetries are statistically and economically insignificant. We also find no asymmetry in the return effect around the S&P 500 benchmark return.

These findings are consistent with individual investors following a naïve reinforcement learning heuristic: investors expect that investments in which they *personally* experienced past rewards will be rewarding in the future, whether or not such a belief is logically justified. Reinforcement learning models have had success in predicting subject choices in experiments (Roth and Erev, 1995; Erev and Roth, 1998). Reinforcement learning is often a sensible heuristic because future rewards *are* positively correlated with recent rewards in many domains. We show in Section IV.A that this relationship does not hold true in 401(k) investing.

Do 401(k) contribution rate changes reflect total savings rate changes? We test this by restricting our sample to participants who at year-end 1998 were contributing less than the threshold to which their employer would provide matching contributions. These participants face instantaneous risk-free marginal returns to saving in their 401(k) of 25% to 100%. It is difficult to imagine that there are alternative investment vehicles that offer comparable risk-adjusted returns. Therefore, these employees have especially strong incentives to adjust their consumption expenditures exclusively through their 401(k) contribution rate. Because Company C did not have a match until 2000, its participants are excluded from this analysis.

The results are in Table III, Panel B. The sample restriction causes us to lose 84% of the sample, which leads to large increases in the standard errors.[8] Nevertheless, the coefficients on the key return and variance variables remain economically large and statistically significant, with higher (absolute value) point estimates in most cases. Comparing Panels A and B, the coefficient on $\Delta R_{i,t}$ increases by an average of about 50 percent across all four specifications, and the magnitude of the coefficients on $\Delta\sigma^2(R_{i,t})$ increase by more than 80 percent. We conclude that the effect is at least as strong among these infra-match investors as it is among the whole sample. Since these investors should be using the 401(k) as their marginal savings vehicle, these results provide evidence that our findings extend to the broader consumption-savings decision.

C. Interactions with age and salary

A key feature of reinforcement learning models is the "Power Law of Practice": reactions to stimuli are large initially and then attenuate as the stock of reinforcements increases and the marginal stimulus constitutes a smaller proportional addition to the stock (Roth and Erev, 1995). Reinforcement learning therefore predicts that the contribution rate of young investors is more responsive to their personal portfolio performance than that of old investors.

The regression in the first column of Table IV tests this prediction by interacting contemporaneous change in 401(k) return and volatility, ΔR and $\Delta\sigma^2(R)$, with de-meaned investor age at year-end 1998. Since Table III shows that lagged volatility change also affects contribution rate changes, we include interactions of this lag with investor age as well. We do not include the lagged return change, which we found to be insignificant in Table III.[9] We

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[8] We drop the lagged return change variable from Panel B, since it was insignificant in Panel A. Inclusion of that variable here does not qualitatively affect the point estimates, but does increase the standard errors.

[9] If we include interactions for lagged return changes, then the point estimates on the other coefficients are not qualitatively affected, but there is an increase in the standard errors for the contemporaneous return interactions.

acknowledge that age may be a proxy for many different things, so the interactions with age may be capturing elements other than learning. We interpret our results here with that caveat in mind.

For brevity, we show only the most comprehensive regression specification that controls for contemporaneous and lagged normalized *CapitalGain*, asset class balance × year dummies, and asset class portfolio share × year dummies. We indeed find that both return chasing and variance avoidance attenuate with age. The age interaction with the contemporaneous change in 401(k) return is significant at the 1% level, as are the age interactions with contemporaneous and lagged volatility changes, which are both significant at the 1% level and of similar magnitudes. Each additional decade of age reduces return chasing by 19% and variance avoidance by 30% relative to the tendencies found in a 21 year old.

Even though responsiveness to portfolio returns decreases with age, investors nonetheless exhibit reinforcement learning behavior for most of their lives. The point estimates indicate that return chasing continues until age 74.[10] Variance avoidance diminishes more swiftly, but both contemporaneous and lagged variance-avoidance persists through age 54.

One might suspect that higher-income investors would be less prone to naïve reinforcement learning, since income is a proxy for financial sophistication. The second column of Table IV examines whether this is the case by interacting contemporaneous and lagged 401(k) return change and volatility change with 1998 log salary. Surprisingly, income has no significant attenuating effect on reinforcement learning tendencies, at least within the low-to-moderate income investor population in our regressions.

The final column of Table IV interacts return and volatility changes with both age and log income. We see that the conclusions drawn from the first two columns are robust to allowing this simultaneous interaction. Age continues to attenuate the force of reinforcement learning, whereas income does not, and the point estimates of the interactions are nearly identical to those in the first two columns.

IV. Alternative explanations

We now consider alternative mechanisms that could generate the return-chasing and variance-avoidance results presented above.

A. Learning about investing skill

Investors who experience high 401(k) returns with low variance may be learning that they have greater skill at 401(k) asset allocation than their coworkers who experience low 401(k) returns with high variance. Therefore, it may be rational for investors with better performance to allocate more to their 401(k).[11] While the vast majority of research in finance would suggest that such skill is rare among individual investors,[12] it is still useful to perform a direct test in our sample.

If a high 401(k) return is a sign of high 401(k) investing skill, then we should see persistence in 401(k) portfolio alphas over time. We regress an investor's portfolio alpha in year t on her portfolio alpha in year $t-1$, where $t = 1998$, 1999, and 2000. Three-factor alphas are

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[10] Age is de-meaned in Table IV to facilitate interpretation of the uninteracted ΔR and $\Delta\sigma^2(R)$ coefficients. The mean age at year-end 1998 in the regression sample is 43.4. Therefore, return chasing drops to zero at age 43.4 + 0.0808/0.0264 × 10 = 74.0 in column 1.

[11] Calvet, Campbell, and Sodini (2009) find that investors stop holding both stocks and bonds after realizing poor mutual fund performance. Because Companies A and E do not offer cash as a 401(k) investment option, one may wonder if our performance-chasing results are caused by investors reducing their 401(k) contributions because they simply want to reduce their risky asset share, rather than because they are shying away from 401(k) investing per se. However, our performance-chasing results are robust to restricting the sample to Companies B, C, and D, which offer cash funds in their 401(k).

[12] See, for example, Benartzi (2001) for evidence that rank-and-file employees do not have the ability to predict their employer's stock return.

calculated by regressing monthly excess portfolio returns on the excess market return and the Fama and French (1993) size and book-to-market factor returns. Four-factor alpha regressions also include Kenneth French's momentum factor (*MOM*) returns. Across our entire sample period, the average alphas are approximately zero: a portfolio that equally weights participant portfolios yields a –1 basis point per month (*t*-statistic = –0.03) three-factor alpha and an 11 basis point per month (*t*-statistic = 0.35) four-factor alpha.

We estimate each persistence regression in two different ways: first, using each investor's alpha as a linear predictor of his or her subsequent year's alpha, and second, allowing the predictive effect of an investor's alpha to differ depending on whether it is positive or negative. Investors' asset allocations are constrained by the investment options offered in their company's 401(k) plan, so it may be sensible to only compare performance relative to other investors in the same company. Therefore, we include company × year dummies as explanatory variables.[13] We cluster our regression standard errors by company × year × employee state of residence to account for the fact that asset allocations (and hence alphas) in our sample may not be independently chosen within a company locality.

Table V shows the results of these portfolio performance persistence regressions. We see that, if anything, a good 401(k) portfolio performance this year predicts *poor* performance the following year. Three-factor alphas are negatively serially correlated, while the four-factor alpha exhibits positive serial correlation that is both statistically and economically insignificant. When we split the alphas into negative and positive cases, we again find no significant evidence of persistent skill. Under the three-factor model, positive alphas predict lower subsequent alphas, while under the four-factor model, negative alphas predict higher subsequent alphas.

[13] Regressions without company × year fixed effects yield qualitatively similar results on alpha persistence.

Overall, there is no empirical support for the hypothesis that returns-chasing and variance-avoidance are driven by rational learning about one's own investing skill.

B. Rebalancing

There is another potential alternative explanation for our finding that 401(k) contribution changes are positively related to portfolio returns: if an investor has significant non-401(k) financial assets, then a positive correlation between 401(k) and non-401(k) asset returns could produce the appearance of return chasing due to rebalancing. For example, suppose all households followed a rule of maintaining a fixed dollar amount in non-401(k) assets (a buffer stock). Then a high 401(k) return would be associated with a high non-401(k) return, which would cause high-return households to increase 401(k) contributions and increase consumption out of non-401(k) assets to bring non-401(k) asset values back down to baseline.

This story, however, is inconsistent with some of our other findings. Such a rebalancing effect should diminish as non-401(k) financial assets get smaller, since the fraction of income required to restore the non-401(k) balance to its steady-state level diminishes for a given percent return. Therefore, the rebalancing story predicts that apparent return chasing would be weakest among the young, who have few financial assets, and strongest among the old. The results presented above in Section III.C, however, showed that the empirical pattern is exactly the opposite: return chasing decreases with age.

Furthermore, most 401(k) households have minimal liquid wealth outside of their 401(k) with which to engage in rebalancing. In the 2001 Survey of Consumer Finances, among 401(k)-holding households earning between $20,000 and $70,000 a year—a sample roughly comparable to the one we use in our analysis—the median household has gross non-retirement financial assets equal to only 2.1 months of income, 76% of which is held in checking, savings, or money market accounts.[14] It is only at the 82nd percentile that households have one year's income in gross non-retirement financial assets. These figures probably overstate outside asset holdings in our sample because the generosity of our 401(k) plans' early withdrawal and loan provisions substantially mitigates the need for a precautionary wealth stock outside the 401(k).[15]

Finally, the rebalancing channel cannot explain the robust variance-avoidance we observe among our investors.

V. Conclusion

We find that individual investors chase their own historical returns and shy away from their own historical return variance when making 401(k) savings rate decisions. This behavior cannot be accounted for by aggregate time fixed effects, employer-specific time fixed effects, investor fixed effects, investor-level income effects, or time-varying investor-level heterogeneity that is correlated with portfolio allocations to stock, bond, and cash asset classes. The observed patterns are consistent with a naïve reinforcement learning heuristic: assets in which one has *personally* experienced success are expected to be successful in the future.

These results contrast with the well-documented reluctance to sell assets that have fallen below their purchase price (Shefrin and Statman, 1985; Odean, 1998), which induces contrarian trading behavior with respect to one's personal return history. This "disposition effect" is

[14] We count CDs, bonds, savings bonds, publicly traded stock, mutual funds, cash value life insurance, other managed accounts, transactions accounts, and miscellaneous assets as non-retirement financial assets.

[15] Table I shows that all of the plans allow participants to take hardship withdrawals from and loans against their 401(k) plan balances, and only one does not allow non-hardship withdrawals. These provisions make 401(k) savings in the companies we study more liquid than for the typical 401(k) participant at the time. The U.S. Department of Labor (2003) reports that in 2000, 40% of full-time employees with savings and thrift plans in private industry were not allowed to take early in-service withdrawals for any reason, and an additional 29% could only take hardship withdrawals. The Profit Sharing/401(k) Council of America (2001) reports that 14% of plans did not permit loans in 2000.

anomalous because the asset's purchase price is investor-specific and already sunk, and hence should not affect the selling decision in the absence of capital gains taxes.[16] The most common explanation for the disposition effect is that prospect theory preferences (Kahneman and Tversky, 1979) cause investors to experience disutility from making a sale below the "reference price" at which they bought the asset (Barberis and Xiong (2008a,b)), and to be risk-seeking for assets that are mentally classified in the loss domain.

We conjecture that the absence of contrarian behavior in our data is due to two factors. First, changing one's ongoing savings rate does not affect whether past investments are psychologically "booked" as a loss. Second, because the 401(k) investments we observe are accumulated through periodic asset purchases that are automatically made each payroll period, it is difficult for the investor to mentally establish a single reference price below which his investment is in the loss domain. Therefore, the tendency to increase one's stake in investments which are underwater is attenuated.

Reinforcement learning is a robust phenomenon because it is often a sensible heuristic; future rewards *are* positively correlated with recent rewards in many domains. Our application may be a rare exception, since we find no evidence that superior performance is persistent. With the exception of momentum returns over some horizons, the finance literature has found scant evidence of persistent alphas in public market investing, so we should not expect persistent alphas among 401(k) participants. Employers and policymakers could try to educate individuals about this counterintuitive fact. However, financial education is costly and has often been found to be ineffective (Choi, Laibson, Madrian, and Metrick (2002), Choi, Laibson, and Madrian (2007, 2008), Cole and Shastry (2007)). Instead, institutional designers may have success in

[16] Introducing capital gains taxes should make investors more prone to sell losers (Constantinides (1984)), which is the opposite of what they actually do.

mitigating the impact of reinforcement learning by muting the reinforcements themselves, perhaps by making short-horizon historical performance less salient in disclosure forms and account statements. Finally, our results provide another argument for programs that provide prominent (non-zero) defaults for savings levels (Madrian and Shea (2004), Choi, Laibson, Madrian, and Metrick (2004)) and savings changes (Benartzi and Thaler (2004)). Sensible defaults combat perverse investment behaviors both by acting as implicit carriers of advice and by utilizing investor inertia to effect sensible outcomes.

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Table I. Company Descriptions, Year-End 2000

Characteristic	Company A	Company B	Company C	Company D	Company E
Industry	Manufacturing	Healthcare	Manufacturing	Utility	Electronics
Number of employees	Over 20,000	Over 50,000	Over 20,000	Over 10,000	Over 10,000
Average age	44.1	42.7	44.6	43.5	39.5
Average salary	$51,835	$33,156	$66,700	$70,069	$54,702
% male	80%	19%	Data unavailable	83%	65%
% married	56%	55%	75%	Data unavailable	50%
401(k) participation rate	80%	61%	86%	85%	83%
Average 401(k) balance	$80,740	$19,501	$81,122	$88,033	$60,426
Maximum contribution rate (% of salary)	10% before-tax, 14% after-tax, 14% combined	15% before-tax	20% before-tax	25% before-tax and after-tax combined	1998-99: 14% before-tax 2000: 16% before-tax
Employer match	25% to 100% (varies by location) of first 6% of pay	25% of first 3% of pay	None until 2000, then 100% of first 1% of pay, 50% of next 4% of pay	50% of first 7% or 8% of pay (depends on union membership)	100% of first 3% of pay, 50% of next 3% of pay
Investment funds	1998: 3 bond, 3 large-cap, 1 mid-cap, 1 small-cap, 3 overseas, employer stock. 1999: Added 1 bond, 1 large-cap, 1 overseas. 2000: Added 1 overseas and self-directed window.	1 cash, 1 bond, 3 pre-mix, 2 large-cap, 1 small-cap, 1 overseas, employer stock	1 cash, 3 bond, 4 pre-mix, 8 large-cap, 5 mid-cap, 3 small-cap, 8 overseas, 3 sector, employer stock	1998: 1 cash, 1 bond, 3 pre-mix, 1 large-cap, 1 mid-cap, 1 overseas, employer stock 1999: Added 1 small cap, self-directed window	1 bond, 3 pre-mix, 5 large-cap, 1 small-cap, 1 overseas
Number of outstanding loans allowed	1 home loan, 1 general purpose loan	1	2	2	2
Hardship withdrawals	Allowed	Allowed	Allowed	Allowed	Allowed
Non-hardship withdrawal rules before age 59½	1 withdrawal allowed per month from after-tax, rollover, vested company match, and profit-share balances	After-tax and vested employer contribution money from grandfathered plans can be withdrawn at any time	Not allowed	After-tax and vested employer match money can be withdrawn at any time	After-tax and rollover balances can be withdrawn at any time

Table II. Summary Statistics

This table presents summary statistics for the regression sample on the year-over-year change in the contribution rate effective during the last pay cycle of December, 401(k) returns, and annual 401(k) dollar capital gains normalized by annual income. Each data point in the distributions represents a separate investor-calendar year combination. The contribution rate change statistics are from year-end 1998 through year-end 2000. The 401(k) return and capital gains statistics are from year-end 1997 through year-end 2000. Capital gains from 1998 to 2000 are normalized by contemporaneous year income, and capital gains in 1997 are normalized by 1998 income due to the lack of 1997 income data.

	Annual contribution rate change (ΔC)	Average monthly return (R)	Monthly return standard deviation ($\sigma(R)$)	Monthly return variance ($\sigma^2(R)$)	Annual capital gains/annual income ($CapitalGain/Y$)
Maximum	20%	10.63%	20.74%	430.10	7.87
99th percentile	9%	6.79%	14.89%	221.69	1.20
90th percentile	2%	2.13%	8.85%	78.24	0.31
75th percentile	0%	1.47%	6.02%	36.28	0.13
50th percentile	0%	0.83%	3.97%	15.73	0.04
25th percentile	0%	0.46%	2.20%	4.85	0.00
10th percentile	0%	-0.46%	0.12%	0.01	-0.08
1st percentile	-9%	-2.24%	0.01%	0.00	-0.56
Minimum	-20%	-6.89%	0.01%	0.00	-8.49
Mean	0.30%	0.99%	4.44%	30.69	0.09
Std. deviation	2.47%	1.41%	3.32%	43.80	0.30

Table III. Regressions of Contribution Rate Changes on Portfolio Returns and Variance

This table presents coefficients from estimating regression equation (3). Panel A contains results for the full sample, and Panel B restricts the sample to those whose contribution rate at year-end 1998 was below the match threshold. The dependent variable is the year-over-year change, in 1999 and 2000, in the contribution rate effective during the last pay cycle of December. The Δ operator is for year-over-year changes. The subscript i indexes investors, and t indexes years. $R_{i,t}$ is average monthly 401(k) percent return, $\sigma^2(R_{i,t})$ is 401(k) monthly return variance, $CapitalGain_{i,t}$ is 401(k) dollar capital gain, $Y_{i,t}$ is annual salary, and $Tenure_{i,t}$ is the number of years since original hire at the end of year t. The last three table rows indicate whether the regression includes company × year dummies, asset class (equities, bonds, or cash) balances at the prior year-end normalized by income interacted with year dummies, and the share of the 401(k) in equities or bonds at the prior year-end interacted with year dummies. The estimates are obtained by differencing equation (3) and running a least squares regression. Standard errors from this differenced regression, clustered by company × employee's state of residence in 1998, are in parentheses below the point estimates.

Panel A: Full sample				
$\Delta R_{i,t}$	0.0933**	0.0939**	0.0995**	0.0847**
	(0.0146)	(0.0192)	(0.0195)	(0.0269)
$\Delta R_{i,t-1}$	0.0107	-0.0026	-0.0122	-0.0119
	(0.0186)	(0.0305)	(0.0323)	(0.0321)
$\Delta\sigma^2(R_{i,t})$	-0.0042**	-0.0042**	-0.0043**	-0.0037**
	(0.0009)	(0.0009)	(0.0010)	(0.0009)
$\Delta\sigma^2(R_{i,t-1})$	-0.0039**	-0.0039**	-0.0045*	-0.0040*
	(0.0014)	(0.0015)	(0.0018)	(0.0017)
$\Delta(CapitalGain_{i,t}/Y_{i,t})$		0.0205	-0.2443*	-0.1849^{+}
		(0.0792)	(0.0992)	(0.0991)
$\Delta(CapitalGain_{i,t-1}/Y_{i,t})$		0.1833	0.5435^{+}	0.5727^{+}
		(0.2165)	(0.2960)	(0.2946)
$\Delta\text{Log}(Tenure_{i,t})$	-1.1663	-1.2711	-1.0891	-1.2210
	(0.9470)	(0.9965)	(0.9756)	(0.9942)
Company × Year dummies	Yes	Yes	Yes	Yes
Balance × Year controls	No	No	Yes	Yes
Share × Year controls	No	No	No	Yes
N	49,248	49,248	49,248	49,248

Panel B: Employees contributing below employer match threshold at year-end 1998				
$\Delta R_{i,t}$	0.1559**	0.1392**	0.1511**	0.0889$^+$
	(0.0417)	(0.0427)	(0.0451)	(0.0507)
$\Delta\sigma^2(R_{i,t})$	-0.0072*	-0.0070*	-0.0071**	-0.0069**
	(0.0027)	(0.0027)	(0.0026)	(0.0024)
$\Delta\sigma^2(R_{i,t-1})$	-0.0043	-0.0050$^+$	-0.0046	-0.0075*
	(0.0030)	(0.0029)	(0.0028)	(0.0033)
$\Delta(CapitalGain_{i,t}/Y_{i,t})$		0.4521	0.2230	0.3264
		(0.2900)	(0.3312)	(0.3337)
$\Delta(CapitalGain_{i,t-1}/Y_{i,t})$		0.8943	1.5746*	1.6414*
		(0.7850)	(0.6789)	(0.6866)
ΔLog($Tenure_{i,t}$)	-1.4529	-0.9717	-1.1692	-1.0817
	(1.3226)	(1.2792)	(1.3939)	(1.3602)
Company × Year dummies	Yes	Yes	Yes	Yes
Balance × Year controls	No	No	Yes	Yes
Share × Year controls	No	No	No	Yes
N	8,050	8,050	8,050	8,050

$^+$ Significant at 10% level. * Significant at the 5% level. ** Significant at the 1% level.

Table IV. Regressions of Contribution Rate Changes on Portfolio Returns and Variance Interacted With Age and Income

This table presents coefficients from estimating a variant of regression equation (3). The dependent variable is the year-over-year change, in 1999 and 2000, in the contribution rate effective during the last pay cycle of December. The Δ operator is for year-over-year changes. The subscript i indexes investors, and t indexes years. $R_{i,t}$ is average monthly 401(k) percent return, $Age_{i,1998}$ is de-meaned age at year-end 1998, $\log(Y_{i,1998})$ is de-meaned log 1998 salary, and $\sigma^2(R_{i,t})$ is 401(k) monthly return variance. All regressions control for contemporaneous and lagged 401(k) dollar capital gains normalized by annual income (*CapitalGain*/*Y*), tenure at company, company × year dummies, 401(k) asset class (equities, bonds, or cash) balances at the prior year-end normalized by income and interacted with year dummies, and the share of 401(k) balances in equities or bonds at the prior year-end interacted with year dummies. The estimates are obtained by differencing the regression equation and running a least squares regression. Standard errors from this differenced regression, clustered by company × employee's state of residence in 1998, are in parentheses below the point estimates.

$\Delta R_{,t}$	0.0808**	0.0932**	0.0831**
	(0.0229)	(0.0265)	(0.0236)
$\Delta R_{i,t} \times Age_{i,1998}/10$	-0.0264**		-0.0257**
	(0.0072)		(0.0075)
$\Delta R_{i,t} \times \log(Y_{i,1998})$		0.0403*	0.0391*
		(0.0175)	(0.0178)
$\Delta\sigma^2(R_{i,t})$	-0.0032**	-0.0036**	-0.0031**
	(0.0007)	(0.0008)	(0.0007)
$\Delta\sigma^2(R_{i,t}) \times Age_{i,1998}/10$	0.0029**		0.0029**
	(0.0005)		(0.0005)
$\Delta\sigma^2(R_{i,t}) \times \log(Y_{i,1998})$		0.6547	0.3132
		(1.2792)	(1.2811)
$\Delta\sigma^2(R_{i,t-1})$	-0.0035**	-0.0039**	-0.0036**
	(0.0013)	(0.0014)	(0.0013)
$\Delta\sigma^2(R_{i,t-1}) \times Age_{i,1998}/10$	0.0033**		0.0033**
	(0.0008)		(0.0008)
$\Delta\sigma^2(R_{i,t-1}) \times \log(Y_{i,1998})$		2.4023	2.0345
		(1.8310)	(1.8510)
CapitalGain/*Y* controls	Yes	Yes	Yes
Tenure controls	Yes	Yes	Yes
Company × Year dummies	Yes	Yes	Yes
Balance × Year controls	Yes	Yes	Yes
Share × Year controls	Yes	Yes	Yes
N	49,248	49,248	49,248

* Significant at the 5% level. ** Significant at the 1% level.

Table V. 401(k) Return Performance Persistence

This table shows the results of regressing year t 401(k) portfolio alpha on year $t-1$ 401(k) portfolio alpha, where t goes from 1998 to 2000. Columns 2 and 4 interact $t-1$ alpha with dummies for whether that alpha is positive or negative. The 3-factor alpha controls for the market return, size effect, and book-to-market effect. The 4-factor alpha also controls for stock price momentum. Standard errors, clustered by company × year × employee's state of residence in year t, are in parentheses below the point estimates.

	3-factor alpha		4-factor alpha	
α_{t-1}	-0.1722**		0.0213	
	(0.0520)		(0.0614)	
$\alpha_{t-1} \times (\alpha_{t-1} \geq 0)$		-0.2389**		0.0912
		(0.0535)		(0.0859)
$\alpha_{t-1} \times (\alpha_{t-1} < 0)$		0.0276		-0.2061*
		(0.0488)		(0.0881)
Company × Year dummies	Yes	Yes	Yes	Yes
N	73,872	73,872	73,872	73,872